

1 "Method of Analysis of Medical Signals"

2

3 This invention relates to a method of analysis of
4 medical signals, and in particular to a method of
5 decomposition of cardiac signals using wavelet
6 transform analysis. Specifically the invention relates
7 to an improved method of resuscitation of patients in
8 cardiac arrest.

9

10 In the UK, coronary heart disease is the second
11 greatest contributor to deaths of people under 75. The
12 social and economic consequences of these death rates

1 are enormous. The current survivability rates of
2 patients after sudden cardiac failure are around 1:10.

3
4 Ventricular tachyarrhythmias, specifically ventricular
5 fibrillation (VF), are the primary arrhythmic events in
6 cases of sudden cardiac death. Administration of
7 prompt therapy to a patient presenting with such
8 symptoms can however lead to their successful
9 resuscitation. Until recently, the only indicators of
10 likelihood of survival of a patient to hospital
11 discharge were traditional variables such as emergency
12 service response time or bystander cardio-pulmonary
13 resuscitation (CPR).

14
15 In most cardiac complaints, analysis of a surface
16 electrocardiogram (EKG) of the presenting patient is a
17 rich source of information. However, until recently, a
18 surface EKG recorded during VF and any subsequent
19 medical intervention to defibrillate, was thought
20 merely to present unstructured electrical activity, and
21 not to provide useful information.

22
23 The first attempts to derive prognostic information
24 from EKGs of the heart in VF focussed on the importance
25 of the amplitude of the waveform defined using peak-to-
26 trough differences in the EKG voltage, measured as
27 either the greatest deflection occurring in a
28 predefined time slot, or as the average peak-to-trough
29 voltage measured over a given time interval. It has
30 been shown that the VF amplitude is inversely related
31 to time elapsed since collapse, is a crude predictor of
32 defibrillation outcome, and is a better indicator of

1 survival to hospital discharge than the traditional
2 variables described above.

3

4 However, recording the VF amplitude accurately is
5 significantly problematical. The EKG voltage amplitude
6 measured during VF is dependent on the direction of the
7 main fibrillation vector and is influenced by a variety
8 of factors including patient chest shape; electrode
9 size; electrode location; and skin/electrode interface
10 resistance. This number of variables makes this
11 amplitude measure both unreliable and inaccurate. That
12 is, although the amplitude of the waveform of an EKG
13 recorded during VF is now recognised to be a crude
14 predictor of the likely outcome of resuscitation of a
15 patient in VF, it is not a reproducible marker of
16 sensitivity to defibrillation, and lacks clinical
17 usefulness.

18

19 In a further development, it is also known to use Fast-
20 Fourier based transforms to generate a frequency
21 spectrum of an EKG in VF to analyse the signal. The
22 median frequency (MF) divides the area under the
23 spectrum into two equal parts. Since this plot is
24 derived from information in both the voltage and time
25 domains, external variables such as lead placement have
26 less effect on the results than the method of observing
27 the amplitude. However, CPR produces artefacts in the
28 recorded EKG signal and, since pausing CPR merely to
29 obtain an EKG signal free of artefacts is likely to
30 compromise resuscitation, these artefacts are
31 necessarily included in this frequency measure, and
32 detract from its usefulness.

1

2 Thus the results of such signal analysis show some
3 correlation with the likely outcome of resuscitation,
4 but again lack sufficient sensitivity and specificity
5 for clinical use. That is, this form of analysis has
6 the disadvantage that, since the Fourier spectrum
7 contains only globally averaged information, specific
8 features in the signal are lost.

9

10 A method of accurate analysis of a surface EKG waveform
11 recorded during VF would therefore be useful in
12 understanding the pathophysiological processes in
13 sudden cardiac death, and thus to produce a model for
14 use:

15

16 in predicting" the efficacy of therapy in individual
17 cases; and

18

19 in determining the selection of the preferred course of
20 primary, and alternative or adjunct therapies thus
21 providing a means for individually tailored therapy for
22 the specific patient needs

23

24 to improve the success rate of resuscitation of
25 patients presenting in VF.

26

27 Atrial fibrillation (AF) is a common cardiac arrhythmia
28 in older people. Atrial fibrillation can be stopped by
29 giving an electric shock to the patient under general
30 anaesthetic (cardioversion). However, many patient
31 return to an AF rhythm soon after treatment. The
32 technology detailed here may also provide a tool to

1 facilitate the clinical evaluation of AF exhibited in
2 the electrocardiogram (EKG) so reducing the risk
3 associated with general anaesthetic in patients where
4 the applied therapy is likely to prove ineffective.

5

6 According to the present invention there is provided
7 a method of decomposition of waveforms in a cardiac
8 signal using wavelet transform analysis.

9

10 The method of the invention is non-invasive, accurate,
11 and capable of delivering real-time information.

12

13 Preferably said method employs discretized wavelet
14 transform analysis to process the EKG.

15

16 Preferably said method employs discretized continuous
17 wavelet transform analysis to process the EKG.

18

19 Preferably said method comprises the steps of deriving
20 the wavelet energy surfaces of an EKG signal; and
21 plotting said wavelet energy surfaces against a
22 location parameter b , and a scale parameter. The scale
23 parameter may be dilation a or band pass frequency f_{bpc} .

24

25 The method initially comprises the steps of connecting
26 electrodes to the presenting patient; and sampling the
27 analogue input signal to derive the cardiac signal.

28

29 Typically said method comprises the step of visually
30 displaying the cardiac signal.

31

1 Said method may display the distribution of energies
2 within the cardiac signal. Said method may display
3 coherent structures within the cardiac signal.

4

5 Said display may be by means of a contour plot. Said
6 display may be by means of a surface plot. Preferably
7 said method provides means to visualise the signal in
8 real-time for clinical use.

9

10 Preferably said method is applicable in the analysis of
11 an EKG in ventricular fibrillation.

12

13 Said method may be applicable in the analysis of an EKG
14 in ventricular fibrillation after the commencement of
15 cardio-pulmonary resuscitation (CPR).

16

17 The method may include the step of disassociating the
18 component features of the temporal trace of a recorded
19 EKG. Additionally or alternatively said method may
20 include the step of temporal filtering of an EKG signal
21 of a heart which is subject to CPR to disassociate the
22 CPR signal from the heart signal.

23

24 Typically said method provides measurable
25 characteristics for the estimation of the health of a
26 heart in VF. Said method may provide measurable
27 characteristics for the estimation of the health of a
28 heart in AF. Said me may provide Typically said method
29 provides measurable characteristics for the estimation
30 of the health of a heart.

31

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1 The method may provide measurable characteristics for
2 the estimation of the time elapsed since the onset of a
3 cardiac incident.

4

5 Typically said method provides measurable
6 characteristics for the estimation of the health of a
7 heart after commencement in CPR.

8

9 Said method may provide a prediction for the outcome of
10 a given therapeutic intervention and so aid the
11 clinical decision making process.

12

13 Said method may provide a basis for individual, patient
14 specific, protocols for therapeutic intervention.

15

16 The method may provide a guide to the optimal timing of
17 defibrillation of a heart in VF.

18

19 Said method may include the step of constructing a
20 damage index for reference purposes. Construction of
21 said index might involve the development of a network
22 classifier from a library of recorded data. Said
23 network classifier may comprise a neural network. Said
24 network classifier may comprise a wavelet network
25 classifier.

26

27 Application of the method of the invention represents a
28 significant advance in coronary care by providing a
29 reliable predictor of the outcome of shocking a patient
30 in VF. In addition, the development of an algorithm
31 using the method of the invention gives the ability to
32 predict shock outcome and to facilitate individual

1 patient therapy. The ability to provide patient
2 specific therapeutic intervention is a priority in the
3 advancement of currently applied medical protocols.
4

5 That is, as discussed above, in certain instances,
6 after prolonged cardiac arrest preceding defibrillation
7 pharmacological measures or CPR can increase the chance
8 of successful resuscitation. Thus, employing the
9 method to predict the outcome of shocking avoids futile
10 defibrillation attempts which can even harm the heart,
11 and can indicate the need for intervention, and
12 influence the selection of the preferred type of
13 intervention, to optimise the metabolic state of the
14 heart prior to counter-shock.
15

16 The predictor algorithm developed using the method is
17 being tested using a new generation of defibrillation
18 devices that have the flexibility to allow easy
19 prototyping of the new defibrillation algorithms.
20

21 According to a further aspect of the present invention
22 there is provided a method of decomposition of
23 waveforms in a cardiac signal using matching pursuit
24 algorithms.
25

26 According to a further aspect of the present invention
27 there is provided an apparatus for decomposition of
28 waveforms in a cardiac signal, said apparatus
29 comprising wavelet transform analysis means.
30

31 Said apparatus may include means to display the
32 distribution of energies within a waveform.

1 Said apparatus may include a monitor adapted to display
2 decomposed waveforms. Said apparatus may be adapted
3 for inclusion in an EKG apparatus.
4

5 According to a further aspect of the present invention
6 there is provided defibrillation means adapted to
7 operate in response to a signal generated by comparison
8 of an EKG trace with decomposed waveform.
9

10 That is, the invention preferably provides a method of
11 wavelet analysis of cardiac signals which provides
12 structural information about the heart - whether the
13 heart is healthy or not - and has significant
14 advantages over fast Fourier transforms.
15

16 The invention may provide a display device in the form
17 of a scrologram that provides real-time visualisation
18 of a wavelet scalogram, showing the distribution of
19 energies and coherent structures within the signal for
20 use as guidance by a clinician.
21

22 The invention may further provide a data analysis tool,
23 which assists in shock timing (atrial pulsing). That
24 is, the derived data may indicate the optimum time to
25 administer shock to the heart. The invention may
26 provide a damage index, preferably in the form of an
27 artificial neural network.
28

29 Preferably the invention provides dissociation of the
30 component features of a temporal trace of a cardiac
31 signal, which may for example be CPR, AF, or cardio-
32 phonographic signals.

1 Embodiments of the invention will now be described by
2 way of example only and with reference to the
3 accompanying drawings in which:

4

5

6 Figure 1a is a Mexican hat wavelet;

7

8 Figure 1b is the real part of a complex Morlet
9 wavelet;

10

11 Figure 2a is a schematic plot showing the dilation
12 of a continuous wavelet;

13

14 Figure 2b is a schematic plot showing the
15 translation of a continuous wavelet;

16

17 Figures 3a to Figure 3e are the plots of the
18 'investigation' of a sinusoidal signal by Mexican
19 hat wavelets of various sizes, showing the effect
20 of translation of the wavelet along the signal
21 (change in b), and dilation of the wavelet (change
22 in a);

23

24 Figure 4a is the plot of five cycles of a sine
25 wave of period P ;

26

27 Figure 4b is the contour plot of $T(a,b)$ against a
28 and b for the sine wave of Figure 4a;

29

30 Figure 4c is the isometric surface plot of $T(a,b)$
31 against a and b for the sine wave of Figure 4a;

32

1 Figure 5a is the plot of a combination of two sine
2 waves of period P_1 , and P_2 , where $P_1 = 5P_2$;

3
4 Figure 5b is the contour plot of $T(a,b)$ against a
5 and b for the sine wave of Figure 5a;

6
7 Figure 5c is the isometric surface plot of $T(a,b)$
8 against a and b for the sine wave of Figure 5a;

9
10 Figure 6a is an EKG trace of a pig heart in sinus
11 rhythm;

12
13 Figure 6b is a 2D energy scalogram associated with
14 the EKG trace of Figure 6a;

15
16 Figure 6c is a 3D energy scalogram associated with
17 the EKG trace of Figure 6a;

18
19 Figures 6d, 6e, 6f and 6g are the energy surface
20 plots from four segments of an EKG signal
21 subsequent to the onset of VF, showing the three
22 dominant ridges A, B, and C appearing in the
23 transform surface, and showing in Figure 6g the
24 onset of CPR after five minutes, associated with a
25 gradual increase in passband frequency of the
26 ridges A, B, and C;

27
28 Figure 7a is an energy scalogram for a pig heart
29 for the first seven minutes of ventricular
30 fibrillation, indicating the initiation of CPR
31 after five minutes;

32

1 Figure 7b is a schematic diagram of the salient
2 features of the scalogram of Figure 7a;

3

4 Figure 7c is the smoothed plot of energy at the
5 8Hz level in the scalogram of Figure 7a against
6 time;

7

8 Figure 8a is a typical segment of an EKG trace of
9 a pig heart in VF;

10

11 Figures 8b, 8c, and 8d are the energy scalograms
12 associated with the trace of Figure 8a;

13

14 Figure 9 is a screen shot of a real time viewer
15 which shows the collected EKG data with its
16 associated wavelet energy display in the form of
17 its energy scalogram, where windows scroll to the
18 right;

19

20 Figure 10a is a 7 second trace of human ECG
21 showing a shock event;

22

23 Figure 10b is a scalogram corresponding to the
24 trace of Figure 10a;

25

26 Figure 11a shows the proportion of energy in
27 scalograms for 120 results (60 ROSC, and 60
28 asystole) at 1.9 Hz after shocking;

29

30 Figure 11b shows the proportion of energy in
31 scalograms for 120 results (60 ROSC, and 60
32 asystole) at 9.3 Hz after shocking;

1

2 Figure 12a is a schematic representation of
3 overlapping signal segments used in a neural
4 network test study;

5

6 Figure 12b shows the weights attributed by the
7 Kohonen network to the 30 frequency levels used in
8 the scalogram;

9

10 Figure 13a is an aorta pressure trace;

11

12 Figure 13b shows the EKG for the same time period
13 as the trace of Figure 13a; and

14

15 Figure 13c is the scalogram associated with the
16 trace of Figure 13a derived from the Morlet
17 wavelet;

18

19 Figure 13d is a detail of the phase part of
20 scalogram Figure 13c;

21

22 Figure 13e is the scalogram associated with the
23 trace of Figure 13a derived from the Mexican hat
24 wavelet; and

25

26 Figure 13f demonstrates the correlation of aorta
27 pressure pulse position with lines of zero phase;

28

29 Figures 14a is the plot of an EKG trace. Figure
30 14b is its associated phase at around 1.5Hz.
31 Figure 14c is its energy scalogram. The
32 correlation of zero phase at this lower frequency

1 and high frequency (low dilation) peaks is thus
2 illustrated.

3

4 Figure 15a shows a 2 second segment of EKG taken
5 from a patient with atrial fibrillation (AF).

6 Figure 15b shows the wavelet scalogram plot
7 associated with this EKG. Figure 15c shows the
8 corresponding modulus maxima of the scalogram of
9 Figure 15b.

10

11 Figure 15d contains a 7 second segment of EKG
12 exhibiting AF. Figure 15e is a trace of EKG
13 temporal components with small amplitude. Figure
14 15f shows the larger magnitude components i.e. the
15 QRS and T waves.

16

17 Figure 15g is a plot of a two second 'blow up' of
18 part of the signal of Figure 15d; Figure 15h is a
19 plot of a two second 'blow up' of part of the
20 signal of Figure 15e; and Figure 15i is a plot of
21 a two second 'blow up' of part of the signal of
22 Figure 15f.

23

24 Referring to the Figures, the present method employs
25 the use of a wavelet transform to analyse a cardiac
26 signal.

27

28 The method involves the decomposition of the signal.
29 This decomposition is accomplished by utilising wavelet
30 transforms to decompose the signal in wavelet space.

31

1 A key distinction between the Fourier analysis of an
2 EKG signal and its analysis by means of a wavelet
3 function is that, whilst the Fourier transform employs
4 a sinusoid function, a wavelet function is localised in
5 time.

6
7 The methodology for such decomposition may include
8 discretized continuous wavelet transforms, orthonormal
9 wavelet transforms of decimated construction, non-
10 decimated wavelet transforms, wavelet packet transforms
11 and matching pursuit algorithms.

12
13 Signal processing employing wavelet transform analysis
14 allows simultaneous elucidation of both spectral and
15 temporal information carried within a signal. Such
16 processing can employ either continuous or discrete
17 transforms. The choice of wavelet transform used for a
18 particular signal processing application depends on
19 factors such as speed of computation necessary, the
20 shape of signal specific features, the frequency
21 resolution required, and the statistical analysis to be
22 performed.

23
24 The preferred method employs the discretized continuous
25 transform as it provides high resolution in wavelet
26 space at lower frequencies.

27
28 This method thus employs the use of a discretized
29 continuous wavelet transform to analyse a cardiac
30 signal.

31

1 In particular, this method employs a wavelet transform
2 as an interrogation tool for EKG signals of ventricular
3 fibrillation.

4

5 A variety of wavelet functions are available, and the
6 most appropriate is selected to analyse the signal to
7 be investigated.

8

9 The wavelet transform of a continuous time signal,
10 $x(t)$, is defined as:

11

$$12 \quad T(a,b) = \frac{1}{w(a)} \int_{-\infty}^{\infty} x(t) \bar{g}\left(\frac{t-b}{a}\right) dt \quad \text{equation 1}$$

13

14 where $g(t-b)/a$ is the analysing wavelet function and
15 $\bar{}$ denotes complex conjugate. $w(a)$ is a scaling
16 function usually of the form $w(a)=a^n$ where n is usually
17 1 or 0.5, and $x(t)$, in this application, is the single
18 channel surface EKG time signal. The transform
19 coefficients $T(a,b)$ are found for both specific
20 locations on the signal, b , and for specific wavelet
21 dilations, a . $T(a,b)$ is plotted against a and b in
22 either a surface or contour plot.

23

24 While other wavelet types may be employed the wavelets
25 mainly used in this method are: the Mexican hat wavelet
26 and the Morlet wavelet, examples of which are shown in
27 Figure 1.

1 The wavelet can translate along the signal (change in
2 b) and dilate (change in a). This is shown
3 schematically in Figure 2 using a Mexican hat wavelet.

4 Figure 3 illustrates the way in which a sinusoidal
5 signal can be 'investigated' at various locations by
6 Mexican hat wavelets of various sizes. The numerical
7 value of the convolution (equation 1) depends upon both
8 the location and dilation of the wavelet with respect
9 to the signal.

10 Figure 3a shows a wavelet of similar 'size' to the
11 sinusoidal waves superimposed on the signal at a b
12 location which produces a reasonable matching of the
13 wavelet and signal locally. From the Figure it is
14 apparent that there is a high correlation between the
15 signal and wavelet at this a scale and b location.
16 Here, the cross correlation of the signal with the
17 wavelet produces a large positive number $T(a,b)$.

18 Figures 3b and 3c show details of the wavelet transform
19 of a signal using a wavelet of approximately the same
20 shape and size as the signal in the vicinity of b .
21 Figure 3b shows a wavelet of similar scale to the
22 sinusoidal waveform located at maximum negative
23 correlation. This produces a large negative $T(a,b)$
24 value. Figure 3c shows a wavelet of similar scale to
25 the sinusoidal waveform located at a position on the
26 time axis where near zero values of $T(a,b)$ are
27 realised. Figure 3d shows the effect on the transform
28 of using the smaller a scale. It can be seen from the
29 plot that the positive and negative parts of the
30 wavelet are all in the vicinity of approximately the

1 same part of the signal, producing a value of $T(a,b)$
2 near zero. Figure 3e shows that the same thing happens
3 when using a much larger wavelet, since the wavelet
4 transform now covers various positive and negative
5 repeating parts of the signal, again producing a near
6 zero value of $T(a,b)$.

7

8 Wavelet transforms are not usually computed at
9 arbitrary dilations for isolated locations in the
10 signal, but rather over a range of a and b . A plot of
11 $T(a,b)$ versus a and b for sinusoidal data using the
12 Mexican hat wavelet is shown in Figure 4. Two methods
13 are then employed to plot $T(a,b)$, namely a contour plot
14 or *scalogram* as shown in Figure 4b, and a surface plot
15 as shown in Figure 4c. At small and large values of a ,
16 the near zero values of $T(a,b)$ are evident from the
17 plots, but at values of a of the order of one quarter
18 of the wavelength of the sinusoid large undulations in
19 $T(a,b)$ correlate with the sinusoidal forms of the
20 signal.

21

22 Figure 5a shows two superpositioned sinusoidal
23 waveforms, the first with period P_1 , the second with
24 period P_2 . $P_1 = 5P_2$. Figures 5b and 5c, the transform
25 plots of the superimposed waveforms clearly show the
26 two periodic waveforms in the signal at scales of one
27 quarter of each period. Thus, Figure 5 clearly
28 demonstrates the ability of the continuous wavelet
29 transform to decompose the signal into its separate

1 frequency components. That is, this transform
2 'unfolds' the signal to show its constituent waveforms.

3 The contribution to the signal energy at a specific a
4 scale and b location is proportional to the two-
5 dimensional wavelet energy density function which is,
6 in turn, proportional to the modulus of $T(a,b)$.

7

8 The method of the present invention thus involves the
9 display of the transform as a contour plot. That is,
10 the method is used to present information derived from
11 an EKG trace of the heart in VF as a scalogram. The
12 preferred form of presenting the information is as an
13 *energy scalogram*, which presents the results as a plot
14 showing the log of the wavelet energy coefficients,
15 against the log of the bandpass centre frequency, f_{bpc} ,
16 of the wavelets for each time increment. The bandpass
17 centre frequency is proportional to the reciprocal of
18 the dilation value, a . This plot highlights small
19 changes in amplitude over the scales of interest. The
20 transform copes with repeating features in time with
21 shifting phase, making it appropriate for real time
22 applications such as this.

23

24 That is, by performing continuous wavelet transform
25 analysis on the ECG in VF, and then by producing an
26 *energy scalogram* of the results, it is possible to
27 unfold the signal in such a way that a previously
28 hidden structure is apparent, in contrast to the
29 apparently disorganised VF signal.

30

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1 The method then includes quantifying the wavelet
2 decomposition. This wavelet decomposition provides
3 both qualitative visual and measurable features of the
4 EKG in wavelet space.

5
6 In practice, surface EKG tracings, recorded as soon as
7 possible after the onset of VF, are analysed.

8
9 As a demonstration of the efficacy of the method, in an
10 example of an experimental procedure utilising this
11 method of analysis employing wavelet techniques, VF was
12 induced in anaesthetised pigs via a pacemaker probe,
13 using a 90V impulse at 60 Hz. All of the pigs remained
14 in VF, untreated for a period of either 3 or 5 minutes.
15 After this time, CPR commenced. The surface EKG
16 (standard lead II) was recorded using needle
17 electrodes. The EKG was sampled at 300 Hz using a 12-
18 bit A to D converter. The method of the present
19 invention was then performed using 32 EKG tracings
20 recorded immediately after the onset of VF.

21
22 Figure 6a represents 4 beats of a pig heart in sinus
23 rhythm. Figures 6b and 6c shows the wavelet transform
24 of the signal displayed in two and three dimensions
25 respectively.

26
27 The QRS complex of the waveform is evident from the
28 conical structures in Figure 6b converging to the high
29 frequency components of the RS spike. The P and T
30 waves are also labelled in the plot. The 3D landscape
31 plot of Figure 6c shows the morphology of the signal in

1 wavelet space. In Figures 6b and 6c the continuous
2 horizontal band (X) is associated with a frequency of
3 1.7 Hz, the beat frequency of the sinus rhythm. The
4 second band (Y) occurs at a frequency of approximately
5 5.1 Hz, corresponding to the separation of the P-QRS-T
6 components in time. At higher frequencies the P, QRS
7 and T components are individually resolved according to
8 their frequency makeup and temporal location.

9
10 Figures 6d to 6g show the energy surfaces for four
11 segments of EKG signal subsequent to the onset of VF,
12 namely: (6d) 0-60 s; (6e) 60-100 s; (6f) 210-240 s;
13 and (6g) 260-360 s.

14
15 The morphology of the VF signal in wavelet space can be
16 seen from the Figures to contain underlying features
17 within a more complex surface topography. The most
18 significant features are the dominant ridges that
19 appear in the transform surface through time.

20
21 Figure 6f shows these ridges quite clearly. A high-
22 energy ridge can be observed at around 10 Hz and two
23 lower energy bands can be observed at lower
24 frequencies. These three ridges are labelled A, B and
25 C, respectively, in the plot. Other ridges are also
26 present within the scalogram.

27
28 The energy surface in Figure 6g contains the onset of
29 CPR after 5 min of untreated VF. The institution of
30 CPR is associated with a gradual increase in the
31 passband frequencies of ridges A, B and C. This change
32 in the composition of the VF signal reflects electrical

1 changes in the fibrillating myocardium associated with
2 the onset of CPR. This is because CPR produces
3 antegrade myocardial blood flow and thus improves the
4 metabolic state of the tissues, temporarily reversing
5 the otherwise progressive decline in high band pass
6 frequency components of the EKG wavelet decomposition.

7
8 Figure 8a is a typical segment of an EKG trace of a pig
9 heart in VF; Figures 8b, 8c, and 8d are the energy
10 scalograms associated with the trace of Figure 8a. As
11 clearly illustrated by these diagrams the principle
12 dilation (band pass centre frequency) component of the
13 scalogram is approximately 10Hz. However, using said
14 method it is also apparent that this component is not
15 constant. It 'pulses' with a degree of regularity. This
16 structure is previously unreported.

17
18 Figure 9 shows similar 'pulsing' in another porcine EKG
19 signal. However, the structure is so pronounced that
20 high energy, high frequency, intermittent components
21 can be observed. These components have an occurrence
22 frequency of the order of the original sinus rhythm:
23 approximately 1.7Hz.

24
25 Figure 10a is a human EKG signal segment containing a
26 shock event. Figure 10b is the corresponding wavelet
27 scalogram. It is apparent from the scalogram of Figure
28 10b that both high frequency spiking and an
29 intermittent high-energy region are present in the
30 vicinity of 10 Hz and also above 10Hz.

31

1 The high frequency spiking is unique to the method of
2 the present invention and is not visible using
3 conventional Fourier techniques. The rich structure
4 made visible within the EKG by the wavelet transform
5 method is evident in the scalogram.

6 It is clearly seen from the Figures that applying the
7 wavelet transform to an EKG signal of VF demonstrates
8 that this signal is a rich source of valuable
9 information. That is, it produces a display showing
10 real time visualisation of the distribution of energies
11 and coherent structures within the signal for use by a
12 clinician in the selection of treatment strategies.

13 Using this method of analysis it is feasible to obtain
14 real-time visual display of the EKG frequency
15 characteristics in the wavelet domain during
16 resuscitation. The scalogram produced provides
17 information about the myocardium that is not available
18 from a standard single channel surface EKG.

19
20 The wavelet scalogram decomposition can be displayed as
21 a real time scrolling window, as shown in Figure 9.
22 This window is useful as an aid for clinical decision
23 making. It can be used as a stand-alone tool, or as
24 basis for on-line statistical analysis of the current
25 state of a heart.

26
27 To produce the window, a MATLAB TM R11 application is
28 used. Each EKG sample taken results in the updating of
29 a FIFO (First In First Out) buffer, and the EKG plot of
30 Figure 9a. The scalogram of Figure 9b is then shifted

1 to the right and clipped before the 'missing' new right
2 hand data is calculated, using conventional matrix
3 algebra, and filled.

4

5 This results in the two scrolling windows of Figure 9.
6 The exponential ramp in the bottom right corner shows
7 the compact support of the wavelet utilised at the
8 given scale.

9

10 Higher resolution scalograms are achieved through
11 implementation on higher specification machines,
12 purpose built hardware, or application specific
13 software with coding using a lower level programming
14 language, such as C++.

15

16 CPR produces artefacts in the EKG signal. Additionally,
17 this method delivers information the value of which is
18 not degraded once the CPR artefacts are filtered from
19 the EKG signal.

20

21 From examination of the *scalograms* shown in Figures 6g,
22 7a and 7b it can be seen that the VF signature and the
23 signature of the CPR artefacts occupy distinct areas of
24 the scalogram, which permits their separation.

25

26 Known techniques such as the Modulus maxima method are
27 now available to reduce the non-zero data points in the
28 wavelet scalogram. This method reduces the topography
29 of the scalogram surface to a series of ridges, thereby

1 considerably reducing the amount of data required to
2 represent the signal in the wavelet space.

3
4 The modulus maxima obtained from a bandlimited signal
5 with a wavelet of finite compact support in the
6 frequency domain defines a complete and stable signal
7 representation.

8
9 In this method, temporal filtering of the original EKG
10 signal to disassociate the CPR signature from the heart
11 signal can either be done directly, using the wavelet
12 *energy scalograms*, or indirectly through modulus maxima
13 techniques. This allows the heart to be monitored
14 without necessitating cessation of CPR to allow rhythm
15 recognition.

16
17 Further to the above, the method may also be applied to
18 patients suffering from atrial fibrillation (AF) as a
19 means of disassociating the prevalent QRS and T waves
20 from the remainder of the signal.

21
22 Wavelet decomposition of the ECG signal is performed
23 using an appropriate wavelet function. The modulus
24 maxima technique is used to encapsulate the scalogram
25 information in a series of ridges. Filtering of the
26 signal is then undertaken using the modulus maxima
27 information and through reconstruction the clinically
28 useful information is isolated from the signal .

29
30 Specifically, Figure 15a shows the wavelet transform
31 decomposition of a 2 second segment of ECG taken from a
32 patient with atrial fibrillation. Below the ECG trace

1 is a wavelet scalogram plot. The corresponding modulus
2 maxima of the scalogram is plotted below the scalogram.
3
4 For example, Figure 15d contains a 7 second segment of
5 ECG exhibiting AF. The signal has been partitioned
6 using a modulus maxima ridge following algorithm. The
7 modulus maxima ridges have been separated into large
8 and small scale features by thresholding the signal at
9 a predetermined wavelet scale. A blow up of part of the
10 signal is given in the lower three plots in the figure:
11 Figures 15g, 15h and 15i. The middle of these plots
12 contains the partitioned signal with the QRS complex
13 and T wave filtered out revealing regular, coherent
14 features that appear at a frequency of approximately
15 400 beats per minute, typical of AF. The lower plot
16 contains the partition with the filtered out QRS and T
17 waves. Although, a relatively simple modulus maxima
18 technique was used in this pilot study whereby the
19 modulus maxima lines were simple partitioned into two
20 subsets, the ability of the technique to separate the
21 signal into QRS and T waves and underlying atrial
22 activity is evident from the results. It is known that
23 the decay in amplitude of a modulus maxima
24 corresponding to a signal feature can be a function of
25 the scale of the wavelet. It is possible to use this
26 property to separate the ridge coefficients into a
27 noisy and coherent part. In this way, further
28 differentiation of the modulus maxima information can
29 be implemented within a more sophisticated algorithm.
30 This will facilitate the further separation of
31 background noise, QRS and T waves, and atrial activity.
32

1 This method thus facilitates useful interpretation of
2 previously unintelligible EKG signals.

3 In patients presenting with uncoordinated rapid
4 electric activity of the ventricle of heart, known as
5 ventricular fibrillation (VF), there is no effective
6 pulse and myocardial blood flow ceases. Even the
7 institution of optimal cardio-pulmonary resuscitation
8 (CPR) of the patient does not achieve more than 30% of
9 the normal cardiac output. Ischaemia during cardiac
10 arrest leads to a rapid depletion of myocardial high-
11 energy phosphates, deterioration of transmembrane
12 potentials, and disruption of intracellular calcium
13 balance. Paradoxically, the myocardium in VF has
14 supranormal metabolic demands. For this reason
15 resuscitation attempts become less likely to succeed
16 with the passage of time, and electrical defibrillating
17 shocks increasingly result in asystole or EMD.

18
19 After prolonged cardiac arrest, the use of
20 pharmacological measures or CPR before attempting
21 defibrillation may increase the chances of successful
22 resuscitation. This invention provides a robust and
23 reliable method of analysis of the state of the
24 myocardium in VF that prevents attempts to defibrillate
25 at times that are unlikely to be successful, or even
26 harmful to the heart. This method also provides an
27 indication of the best way in which to optimise the
28 metabolic state of the heart prior to counter-shock.
29

1 The method includes steps to establish a standard
2 against which to evaluate collected data in a
3 particular incidence.
4

5 The method further employs use of measurable signal
6 characteristics derived from the position and amplitude
7 of features in the *scalogram* to estimate both the
8 condition of the myocardium, and downtime of the
9 subject while in VF.
10

11 The method thus provides for optimal treatment of the
12 heart in VF, so fulfilling specific patient needs, by
13 therapeutic intervention, if appropriate.
14

15 An energy scalogram such as that shown in Figure 7
16 displays three distinct bands, labelled A, B, C. It is
17 possible to derive quantifiable measures using
18 correlations between the location and energy content of
19 the bands.
20

21 Band A of Figure 7b represents the dominant energy band
22 seen in the *scalogram* of Figure 7a, and corresponds to
23 the tachycardic beating of VF. However the *scalogram*
24 is much more informative in that it also shows, as
25 bands B and C, the behaviour of other frequency
26 components of the signal which were previously
27 unreported.
28

29 Figure 7a shows a 2D *energy scalogram*. It includes the
30 first 5 minute period of VF, followed by a 2.5 minute
31 period of CPR. The onset of CPR is clearly identified
32 by the distinct horizontal dark band in the lower right

1 quadrant of the Figure. Over the first 5 minute
2 period, three bands, labelled A, B, C, can be clearly
3 seen in the scalograms. These bands correspond to the
4 ridges of Figures 6d to g. The increase in the
5 frequency components of these three bands after the
6 onset of CPR is evident in the plot. Bands B and C
7 follow trajectories similar to each other in the
8 scalogram, reducing in frequency over time. Band A,
9 however, moves independently of the other two.
10 Initially Band A increases, then it decreases to a
11 local minimum value at approximately 70s. Between 70
12 and 160s it increases relative to Bands B and C.
13 Finally, it decreases until the start of CPR after
14 300s. The same pattern was present in all 32 pig EKG
15 traces of the experiment.

16
17 Obvious increases in the passband frequency of all
18 three bands are observed in the scalogram after the
19 onset of CPR. For some of the signals studied this
20 increase in band C is masked by the dominant CPR band,
21 and thus cannot be seen in the scalogram.

22
23 Figure 7b provides a schematic diagram of the salient
24 features contained within the scalogram plots, where t_0
25 is immediately after the onset of VF; t_2 is the start
26 of CPR; and t_3 is the end of the analysis. Figure 7c
27 shows the relative proportion of energy contained in
28 the scalogram in the 5 to 12 Hz region through time.
29 There is an obvious decay in the relative energy
30 associated with this region which is associated with
31 the breakdown of co-ordinated activity in the heart.
32

1 The steps of the method of the present invention
2 described above establish that during the course of VF
3 there is a reduction in the proportion of energy within
4 the dominant frequency band indicated in Figure 7c.
5 This dominant frequency band, Band A in Figure 7a, is
6 demonstrated to be approximately 10 Hz for pig VF.

7
8 The energy within this band changes rapidly. This is
9 illustrated by the 'pulses' in Figures 8,9,10.

10
11 The Figures 6,7,8,9,10 show that applying the wavelet
12 transform to an EKG signal of VF demonstrates that this
13 signal is a rich source of valuable information.

14
15 The underlying hypothesis of the method of the present
16 invention is that the scalogram associated with an EKG
17 correlates to the state of the myocardium as it decays
18 subsequent to the onset of VF.

19
20 The method uses the information contained in the energy
21 scalogram associated with an EKG to predict the likely
22 success of clinical intervention, namely shocking.

23
24 It is therefore possible to develop a wavelet transform
25 based tool for the prediction of shock outcome during
26 ventricular fibrillation by:

- 27
- 28 1. collecting and collating data from sets of
29 archived EKGs recorded from humans in VF where
30 attempts to resuscitate by shocking were made; and
31
 - 32 2. developing a classifier for reference purposes.

1
2 Figure 11 is a classification of the shock outcome in
3 either asystole or a rhythmic response using a
4 relatively simple statistical analysis. The experiment
5 yielding the results to compile these Figures involved
6 use of the lead II outputs of standard three lead EKGs
7 of 120 patients in VF. Each trace is of three second
8 duration sampled at 100 Hz. Of these patients, 60
9 returned to sinus rhythm while the other 60
10 deteriorated to asystole, post shock.

11
12 Each trace was decomposed into an associated wavelet
13 transform from which its energy scalogram was
14 generated. The volume under this surface was then
15 normalised to render the results independent of signal
16 amplitude, but instead the result of the relative
17 wavelet constituents of the signals. The log of the
18 mean values at each dilation (band centre frequency)
19 for each was then recorded. Figures 11a and 11b show
20 the distribution of energies in a lower frequency band
21 (1.9 Hz) and at the 9.3 Hz band. Clearly, through
22 visual inspection, it is apparent that the proportion
23 of energies around the 10 Hz band is higher for
24 successful defibrillation attempts.

25
26 The method then extends to apply neural techniques to
27 analysis of wavelet pre-processed EKG signals.

28
29 A pilot study conducted to determine the feasibility of
30 using artificial neural techniques to provide a tool to
31 predict the outcome of defibrillation during VF used
32 eight human EKG trace segments containing shock events.

1 In these cases, the result of shocking was unequivocal
2 - four patients returned to VF, and four experienced
3 return of spontaneous circulation (ROSC).

4
5 The traces were transformed using the Morlet wavelet,
6 and energy scalograms containing thirty frequency
7 levels were produced. This was then split into eight
8 overlapping sections as shown in Figure 12a, each of
9 200 points (2/3 seconds duration). These 200 location
10 points were subsampled down to 50 to give eight
11 scalograms for each trace of 50 x 30 elements. The
12 volume under the energy scalograms were normalised and
13 the patterns fed into a 'winner take all' Kohonen
14 network with two output units and built in conscience
15 (to avoid local minima). That is, the network was
16 asked to group the 64 input patterns into two classes.
17 All but ten outputs were collectively classified
18 correctly giving a mean pattern error of 0.156 (against
19 0.5 average pattern error expected from random inputs).

20
21 Since this is a vector quantisation method (VQM) it was
22 possible to identify how the network differentiates the
23 patterns through inspection of its connective weights.
24 The weights from each location position across all
25 scales in the network are approximately the same, which
26 means that there are no markers with which to
27 synchronise the different pre-processed traces. This
28 confirms that this neural network is too simple for
29 this purpose. That is the network is not equipped to
30 'consider' the relative phase of each input pattern.

31

1 Figure 12b shows the weights for the 'success' (ROSC)
2 and 'failure' (VF) to the output units from the first
3 two time slices across all scales. The weights
4 indicate the classes are differentiated by the
5 proportion of energy in the lower scales, which can be
6 seen when compared with Figure 11.

7
8 Although the above described method indicates the
9 slight drop in the dominant frequency expected, the
10 drop is very marginal which leads to the conclusion of
11 the lack of competence of previously proposed methods
12 as a defibrillation success predictor.

13
14 In summary, a library of human ECG data containing data
15 sets of human VF with attempts to resuscitate by
16 shocking is used as a database. This database is
17 extended to include data sets containing various
18 methods of shocking including, for example, biphasic
19 shocking. The biphasic shock waveform has resulted in
20 an increased proportion of successful defibrillation
21 attempts and is set to become the standard treatment
22 for cases of VF.

23
24 In one example, the recognised outcomes are defined by
25 trace components of the post-shock window lasting until
26 next shock (if present). If the ratio of the given
27 rhythm exceeds 10% of the total window length the
28 rhythms are prioritised according to the sequence:

29
30

Class	Rhythm	Ratio
1	Pulse (SVR)	+10%

1	2	No pulse (EMD)	+10%
2	3	Isoelectric (Asystole)	+10%
3	4	VF	+10%

4

5

6 Class 5 is the class of VF preceding shocks where VF
7 re-establishes itself within 5 seconds following the
8 shock (i.e. no change). The VF in all the other
9 classes were non-VF in this period.

10

11 Wavelet analysis of this information in accordance with
12 the method of the invention is then performed to:

13

14 construct a wavelet visualisation of the signal -
15 usually by plotting wavelet energy surfaces against the
16 location parameter *b* and the inverse of the dilation
17 parameter *a*;

18

19 provide measurable characteristics of the signal for
20 estimation of downtime of the patient;

21

22 provide measurable characteristics of the signal for
23 determining the health of the heart post CPR; and

24

25 to construct energy scalogram devised for the method -
26 which uses the energy density function and the
27 reciprocal of the wavelet *a* scale for use as a
28 predictor tool.

29

30 As described above it is possible to use artificial
31 neural network based techniques to develop such an
32 indication of the state of myocardium. In the

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1 alternative, it is possible to classify the wavelet
2 scalogram through multilayered feedforward network
3 types.

4

5 The method may include the development of a modulus
6 maxima algorithm tool for the preprocessing of ECG
7 prior to its input into a neural network classifier.

8

9 Using this technique improves network performance
10 whether this data is further encoded, or presented as a
11 whole, larger, sparse matrix as a pattern in the input
12 space.

13

14 This method therefore utilises the generalisation
15 properties of a feed forward multi-layer network to
16 predict the likelihood of defibrillation success from
17 the wavelet transform of the EKG traces. This multi-
18 layer network with its relatively simple dynamics, when
19 combined with wavelet pre-processing, has proved itself
20 a useful tool as a universal approximator.

21

22 The classes of multi-layer network types of use in this
23 method are:

24

- 25 • Multi-layered feed forward (MLFF) neural networks
26 with back propagation training and monotonic
27 activation functions; and
- 28 • Radial Basis Neural Networks (RBNN) as have
29 previously been successfully applied to the denoising
30 of medical Doppler ultrasound signals with wavelet
31 preprocessing.

1

2 As described above, the method involves the
3 decomposition of EKG signals into a complete basis set
4 defined by the wavelet shape and other parameters by
5 salient basis functions of a different basis set,
6 converged upon through regression techniques (sigmoid
7 in the case of multilayer neural networks, Radial basis
8 etc).

9

10 These regression techniques can also be used to
11 construct a wavelet basis function set directly.

12

13 Methodologies for restricting the search space of the
14 wavelet basis functions considered are known. Whilst
15 this wavelet network has been shown to be effective for
16 chaotic time series prediction, its implementation
17 involves the use of wavelet frames of a decimated,
18 dyadic, construction. The method of the present
19 invention may employ continuous wavelet networks
20 spanning a redundant wavelet basis which, although
21 computationally more expensive, overcomes the time
22 invariance constraint and the limited size of input
23 space associated with use of wavelet frames.

24

25 The method may use conventional gradient decent methods
26 to produce a single layer wavelet classifier.

27

28 These wavelet networks may be further employed as part
29 of a multilayer system as a non-parameterised estimate
30 of the original trace for input to further hidden
31 layers.

32

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1 The network type of choice for the automated prediction
2 system of the method is selected on the basis of its
3 sensitivity and selectivity in correctly classifying
4 successful defibrillation outcomes in test set data,
5 since this is most clinically useful.

6

7 Thus experimental comparison of the three techniques
8 demonstrates the efficacy of the wavelet transform
9 technique.

10

11 The nature of underlying atrial activity can also be
12 determined from wavelet decomposition of the EKG
13 signal. The wavelet function gives information
14 regarding the amplitude and, where appropriate, phase
15 of the transformed signal. It is known that pressure
16 readings taken from the aorta correlate to forms of
17 atrial activity within the heart. Areas of localised
18 high energy contained within the scalogram can be
19 demonstrated to correlate with these pressure readings.
20 This experimental result is extrapolated to mean that
21 areas of localised high energy contained within the
22 scalogram correlate with forms of atrial activity
23 within the heart.

24

25 Figure 13a shows the aorta pressure, Figure 13b the EKG
26 trace, for the same time period as Figure 13a, and
27 Figure 13c shows the scalogram for the EKG of Figure
28 13b. It is apparent that there is an increase in
29 energy in the system during an atrial pulse, indicated
30 by the dark blotches occurring in the scalogram at an
31 f_{bpc} of around 10 Hz. There is a frequency component
32 between 1 and 2 Hz. As shown in Figure 13d, which

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1 highlights the phase of the scalogram between 1 and 2
2 Hz, it is apparent that the lines of zero phase are in
3 alignment with the atrial pulse.

4

5 In a further scalogram, shown in Figure 13e, produced
6 by using the Mexican hat wavelet transform which is
7 real and has better temporal resolution, but worse
8 frequency resolution than the complex scalogram of
9 Figure 13c, it is demonstrated that positive high
10 amplitude components are shown at the same positions
11 for scales of between 1 and 2 Hz, thus reinforcing the
12 findings extrapolated from Figure 13c. That is as
13 shown in Figure 13f, the lines of zero phase correlate
14 with the pulse position.

15

16 The lines of zero phase within the 1.8Hz frequency band
17 also align with regular peaks in the scalograms, as
18 shown in Figures 14a, 14b & 14c. This links the
19 presence of the 1.8 Hz band with the observed peaks at
20 higher frequencies. This correlation between the 1.8
21 Hz band and the aorta pressure pulse suggests atrial
22 activity is present.

23

24 In a further application of the method, means for
25 identifying the optimum timing for application of the
26 defibrillation shock can be extrapolated from the
27 pulsing identified by the wavelet technique and shown
28 in Figures 8, 9, 10, and 14, by comparison with traces
29 of attempts at defibrillation which initially fail but
30 are subsequently successful.

2 Thus, any data sets, in the above, that correspond to
3 multiple shocking of the same patient, where
4 defibrillation has been repeatedly attempted are
5 considered separately since these traces hold important
6 information.

8 The pilot study detailed above used Morlet wavelet
9 based energy scalogram decomposition of signal segments
0 immediately prior to shocking. A full parametric
1 wavelet study of the method determines the optimum
2 method.

14 The method includes the development of a classifier
15 using the wavelet transform analysis.

```
17 Various types of neural network classifier are
18 achievable using this method.
```

20 The linkage of shock timing to the phase information of
21 wavelet components allows for increased defibrillation
22 success and reduced shock energies. The wavelet-
23 derived information can also be employed to predict the
24 likelihood of shock success, preventing futile or
25 harmful defibrillation attempts, and providing a
26 predictor of an optimal resuscitation strategy or
27 strategies.

29 This method demonstrates the utility of the wavelet
30 transform as a new method of EKG signal analysis during
31 VF. It provides a robust, real-time solution to the

1 problem of useful monitoring of the myocardium during
2 resuscitation.

3

4 When compared with conventional statistical methods,
5 such as fast Fourier transforms, it is seen that the
6 temporal resolution of the wavelet technique gives a
7 scalogram which better describes the non-stationary,
8 intermittent, nature of the EKG trace to be analysed,
9 and gives a method of greater predictive effectiveness
10 than is already known. The effectiveness criteria for
11 the networks of the method of the present invention are
12 based upon their sensitivity and selectivity in
13 correctly classifying successful defibrillation
14 outcomes from test data sets.

15

16 Although this description refers to wavelet transform
17 analysis, this term is to be construed to include
18 matching pursuit algorithms and similar analysis
19 techniques.

20

21 Modifications and improvements can be made to the above
22 without departing from the scope of the invention.